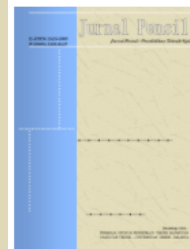


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LATENT HETEROGENEITY IN DECISION MECHANISMS FOR FUTURE ELECTRIC VEHICLE PURCHASE AMONG CURRENT OWNERS: A FIMIX-PLS ANALYSIS

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Abstract

Future electric vehicle (EV) purchase intention among current owners may be formed through different decision mechanisms even when an aggregate structural model produces stable average coefficients. This study examines unobserved heterogeneity in a survey of 521 current EV owners in Jabodetabek, Indonesia. The aggregate PLS-SEM model is retained only as the analytical baseline, whereas finite mixture partial least squares (FIMIX-PLS) is used to compare latent structural solutions with two, three, and four segments. The three-segment solution was retained because BIC (2677.79) and CAIC (2739.79) reached their lowest values at three segments, and the estimated mixture proportions (53.0%, 37.8%, and 9.2%) were less imbalanced than the two-segment solution (89.9% and 10.1%). AIC3 favoured four segments, whereas entropy and NFI favoured two; the retained solution is therefore a model-selection compromise rather than a uniquely determined partition. In the two larger segments, perceived behavioural control had the largest proximal coefficient in Segment 1 ($\beta = 0.497$), whereas subjective norm had the largest coefficient in Segment 2 ($\beta = 0.468$). The smallest segment had near-perfect explained variance for purchase intention ($R^2 = 0.9998$) and a residual variance of 0.001, so its coefficients are interpreted cautiously. The analysis adds segment-specific information to the aggregate model but does not establish statistically significant differences between segment coefficients.

Keywords: Electric Vehicle, Future Purchase Intention, Current EV Owners; Latent Heterogeneity; FIMIX-PLS

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Introduction

Current EV owners evaluate a future vehicle purchase from a different experiential position than prospective first-time buyers. Direct experience exposes owners to charging routines, vehicle range, operating cost, maintenance, and everyday usability, so post-adoption evaluation can differ from pre-adoption expectations (Bühler et al., 2014; Graham-Rowe et al., 2012; Günther et al., 2019). The outcome examined here is future EV purchase intention among current owners, which may refer to replacement, repurchase, or an additional EV. Because the questionnaire did not distinguish those purchase contexts, the construct is interpreted as a prospective purchase intention among owners rather than as first-time adoption intention.

The aggregate behavioural model combines the Theory of Planned Behaviour (TPB), Theory of Consumption Values (TCV), and Protection Motivation Theory (PMT), with technological uncertainty as a moderator. TPB positions attitude, subjective norm, and perceived behavioural control (PBC) as proximal determinants of intention (Ajzen, 1985; Wang et al., 2016), while TCV separates functional, social, emotional, epistemic, and conditional value in consumer choice (Sheth et al., 1991). PMT distinguishes threat appraisal from coping appraisal through perceived vulnerability, severity, response efficacy, and response cost (Prentice-Dunn & Rogers, 1986). These theories are retained as the aggregate behavioural baseline; the present paper does not claim theoretical novelty from integrating them.

Aggregate PLS-SEM estimates a single set of structural coefficients for the full sample. When structural relationships are heterogeneous, these aggregate estimates can conceal differences across unobserved subpopulations (Ringle et al., 2015). This issue has motivated the use of segmentation approaches to examine heterogeneity within PLS-SEM models (Joshi & Chawla, 2023).

Heterogeneity is also relevant in the EV context. EV purchase intention has been shown to vary across consumer characteristics and decision contexts (Champahom et al., 2024). Economic conditions can contribute to differences in how consumers evaluate EV adoption (Chanda et al., 2024). Technology-related uncertainty provides another source of variation in EV evaluation (Lazuardy et al., 2024). Other EV studies have identified differences associated with demographic and contextual characteristics (Alzoubi et al., 2025).

Practical conditions also differ across EV users. Travel demand and household circumstances can affect mobility requirements and EV suitability (Gan et al., 2020). Range requirements can alter the constraints users associate with EV use (Mao et al., 2025), while differences in infrastructure exposure can affect the conditions under which EV ownership and use are evaluated (Malabanan et al., 2025). These observed differences provide a basis for expecting heterogeneity among EV users. They do not, however, establish that the structural coefficients linking behavioural constructs differ across latent groups.

Latent segmentation addresses this problem without defining groups in advance from observed demographics. FIMIX-PLS estimates mixture components from differences in the structural model itself (Ringle et al., 2015). Related EV studies have used clustering or latent-class approaches to identify differences in consumer profiles, charging styles, preferences, and purchase-intention patterns (Hajhashemi et al., 2024; Morton et al., 2017; Zuo et al., 2025). Recent work also shows that rational and normative determinants can vary across EV decision contexts (Cabeza-Ramírez et al., 2025). The distinction is important: observed profiling describes who differs, whereas finite-mixture analysis tests whether the relationships among behavioural constructs differ across unobserved groups.

The unresolved question is whether the proximal mechanisms that form future EV purchase intentions are sufficiently homogeneous among current EV owners. Charging access can shape the practical conditions under which EV use is evaluated, particularly when drivers depend on public or fast-charging infrastructure (Neaimh et al., 2017). Driving range can also affect EV evaluation when users anticipate longer or less predictable travel requirements (Egbue & Long, 2012). Travel distance and mobility requirements may further alter the perceived practicality of EV

ownership and use (Jia & Chen, 2022; Oh et al., 2026). Infrastructure availability and accessibility can vary across locations and user circumstances, creating different operating conditions for EV users (Karmaker et al., 2025; Malabanan et al., 2025). These studies provide a contextual basis for expecting heterogeneous evaluations. They do not, however, establish that the structural coefficients linking attitude, subjective norm, and perceived behavioural control to future EV purchase intention differ across latent groups. The analysis therefore compares two-, three-, and four-segment FIMIX-PLS solutions and then examines segment-specific proximal coefficients.

The objective is to identify latent structural heterogeneity in future EV purchase intention among 521 current EV owners in Jabodetabek. The aggregate PLS-SEM model serves only as the baseline, while the contribution of this paper lies in comparing latent mixture solutions and describing how the proximal TPB coefficients vary across the retained segments. This focus extends prior work that documents user heterogeneity through demographic, preference, or charging profiles by testing heterogeneity in the structural decision mechanism itself (Champahom et al., 2024; Hajhashemi et al., 2024; Zuo et al., 2025).

The analysis does not infer segment-specific differences in charging access, mobility patterns, infrastructure exposure, TCV constructs, or PMT constructs unless those quantities are reported at segment level. Charging conditions, travel patterns, and system support remain relevant contextual factors in EV use and adoption (Foley et al., 2020; Sierzechula et al., 2014), but the FIMIX evidence reported here is limited to latent differences in the estimated behavioural structure.

Research Methods

This study used a cross-sectional quantitative survey to examine future EV purchase intention among current EV owners in Jabodetabek. The target population was current EV owners residing in the study area. Respondents were recruited purposely through EV-owner communities, social media, automotive forums, and EV-user networks because a complete sampling frame of EV owners was not available. Current EV ownership was required for inclusion. Data were collected from 1 July to 31 October 2025 using a structured questionnaire, and 521 usable responses were included in the analysis. Before completing the questionnaire, prospective respondents were informed about the study and were given instructions regarding participation and questionnaire completion. Participation proceeded after respondents indicated their willingness to take part in the survey. A pilot survey involving 48 respondents was conducted before the main survey to refine the instrument. Because recruitment was nonprobability-based, the results describe relationships within the recruited owner sample and should not be interpreted as population estimates for all EV owners in Jabodetabek.

Sample-size adequacy was evaluated in relation to the complexity of the PLS-SEM model and the subsequent mixture analysis. Current PLS-SEM guidance cautions against using the 10-times rule as the sole basis for sample-size justification and recommends power-based or more precise minimum-sample approaches where possible ((Kock & Hadaya, 2018; Sarstedt et al., 2022). No prospective power calculation was conducted for this study; therefore, the achieved sample of 521 respondents is reported directly rather than presented as a sample size derived from an a priori power analysis. For the FIMIX-PLS analysis, component size was evaluated together with the information criteria and classification measures because finer mixture solutions allocate observations to progressively smaller components, which can affect the stability and substantive interpretation of segment-specific estimates (Hair et al., 2019; Matthews et al., 2016).

Outcome definition

The dependent construct is future EV purchase intention among current EV owners. Because every respondent already owned an EV at the time of the survey, the outcome represents intention to make a future EV purchase rather than first-time EV adoption. The questionnaire did not distinguish whether that future purchase would replace the current EV, constitute a repurchase, or add another EV to the household. These possibilities were therefore retained within a single prospective purchase-intention construct.

Measurement and analytical procedure

The model contains 14 reflective constructs measured by 52 indicators using five-point Likert-type response scales. The Theory of Consumption Values is represented by functional, emotional, social, epistemic, and conditional value. Protection Motivation Theory is represented by perceived vulnerability, perceived severity, response efficacy, and response cost. The Theory of Planned Behavior is represented by attitude, subjective norm, perceived behavioral control, and future EV purchase intention, while technological uncertainty is included as a moderator. The aggregate measurement and structural models were estimated in SmartPLS 4. Measurement-model assessment examined indicator loadings, composite reliability, average variance extracted (AVE), and heterotrait-monotrait ratios (HTMT). The structural assessment examined inner VIF, R^2 , effect sizes, predictive metrics, and bootstrapped path coefficients. HTMT < 0.90 was used as a screening criterion for discriminant validity, supplemented by bootstrap confidence intervals for pairs close to the threshold. Statistical inference used 5,000 bootstrap samples, percentile confidence intervals, two-tailed testing at the 5% significance level, and a fixed seed. These reporting choices follow current PLS-SEM guidance, which emphasizes explicit assessment of measurement quality, structural relationships, predictive performance, and robustness rather than reliance on a single overall fit statistic (Hair et al., 2019).

FIMIX-PLS procedure

FIMIX-PLS was applied to examine unobserved heterogeneity in the structural relationships. The procedure estimates finite-mixture components from the structural model rather than forming groups from observed demographic characteristics (Hair et al., 2012; Matthews et al., 2016). Two-, three-, and four-segment solutions were estimated using a maximum of 5,000 iterations, 15 repetitions, a fixed seed, and a stopping criterion of 10^{-7} . All 15 repetitions reached convergence, although repetitions converged to several local likelihood solutions; the reported specification corresponds to the best log-likelihood solution. Model comparison considered AIC3, BIC, CAIC, MDL5, normed entropy (EN), NFI, and estimated segment proportions. Because the criteria did not identify the same number of segments, the retained solution was selected from their joint pattern rather than from a single index. Segment size was also considered because increasingly fine mixture solutions partition the total sample into smaller components, which can limit the reliability and substantive interpretation of segment-specific estimates (Matthews et al., 2016).

The present study uses the same 521-owner dataset as a separate aggregate PLS-SEM analysis conducted by the authors. In this paper, aggregate estimates are reported only as the analytical baseline for examining latent heterogeneity. The distinct contribution is the comparison of FIMIX solutions and segment-specific structural coefficients. Sample-size adequacy was considered in relation to the complexity of the PLS-SEM model and the subsequent mixture analysis. Current PLS-SEM guidance cautions against using the 10-times rule as the sole justification for sample size and recommends power-based or more precise minimum-sample approaches where possible (Kock & Hadaya, 2018; Sarstedt et al., 2022).

Research Results and Discussion

Respondent profile

The sample consists of 521 current EV owners in Jabodetabek. Men account for 70.4% ($n = 367$) and women for 29.6% ($n = 154$). Respondents younger than 35 account for 36.9% ($n = 192$), those aged 35–55 for 59.1% ($n = 308$), and those older than 55 for 4.0% ($n = 21$). Monthly income is below IDR 20 million for 47.6% of respondents, IDR 20–40 million for 27.6%, and above IDR 40 million for 24.8%. These figures describe the purposively recruited sample; they do not estimate the demographic composition of all EV owners in Jabodetabek.

Table 1. Respondent Profile

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	367	70.4
	Female	154	29.6
Age Group	Under 35 years old	192	36.9
	35–55 years old	308	59.1
	Above 55 years old	21	4.0
Income Level	Under 20 million IDR	248	47.6
	20 – 40 million IDR	144	27.6
	Above 40 million IDR	129	24.8
Residence	Jakarta	163	31.3
	Tangerang (including South Tangerang)	199	38.2
	Bekasi	72	13.8
	Bogor	48	9.2
	Depok	39	7.4

Measurement Model

The measurement model met the construct-level criteria for reliability and convergent validity. Composite reliability values exceeded the recommended threshold, and all AVE values were above 0.50. Most indicator loadings also exceeded 0.70, although FV3 at 0.632 and CV5 at 0.693 fell below that preferred level. Both indicators were retained because their respective constructs still met the reliability and AVE criteria, and removing them would narrow construct coverage. Technological uncertainty had a composite reliability of 0.831 and an AVE of 0.624, with loadings ranging from 0.707 to 0.885. Table 2 provides the complete measurement-model results.

Discriminant validity required closer examination. Most HTMT values remained below the 0.90 screening threshold, but the attitude–PBC pair reached 0.904. Bootstrap inference based on 5,000 samples produced a 95% percentile confidence interval from 0.849 to 0.957, so the interval did not include 1.00. The attitude–response efficacy pair was also close to the screening threshold, with an HTMT value of 0.896 and a 95% interval from 0.834 to 0.953. These results do not justify treating the constructs as indistinguishable, but they do warrant caution when interpreting their empirical separation. The corresponding HTMT estimates appear in Table 3. Collinearity did not indicate a critical problem in the structural model. Direct relationships produced VIF values between 1.023 and 2.644. The interaction terms were higher, with values of 3.221 for technological uncertainty $\times$ attitude, 3.664 for technological uncertainty $\times$ PBC, and 2.085 for technological uncertainty $\times$ subjective norm. Because all values remained below 5, the model did not meet the usual criterion for problematic collinearity. Table 4 reports the full set of VIF estimates.

Table 2. Measurement Model Results

Variables	Item	loading	CR	AVE
Functional Value (FV)	FV1	0.750	0.850	0.576
	FV2	0.856		

Variables	Item	loading	CR	AVE
Emotional Value (EV)	FV3	0.632	0.869	0.689
	FV4	0.815		
	EV1	0.797		
	EV2	0.868		
Social Value (SV)	EV3	0.824	0.921	0.745
	SV1	0.837		
	SV2	0.881		
	SV3	0.900		
Epistemic Value (EP)	SV4	0.834	0.866	0.619
	EPV1	0.738		
	EPV2	0.729		
	EPV3	0.838		
Conditional Value (CV)	EPV4	0.834	0.871	0.576
	CV1	0.745		
	CV2	0.833		
	CV3	0.792		
	CV4	0.721		
Perceived vulnerability (PV)	CV5	0.693	0.906	0.762
	PV1	0.883		
	PV2	0.908		
Perceived severity (PS)	PV3	0.826	0.876	0.702
	PS1	0.832		
	PS2	0.865		
Response efficacy (RE)	PS3	0.816	0.881	0.713
	RE1	0.762		
	RE2	0.888		
Response cost (RC)	RE3	0.877	0.805	0.674
	RC1	0.780		
Technological uncertainty (TU)	RC2	0.861	0.831	0.680
	TU1	0.767		
	TU2	0.707		
Attitude (ATT)	TU3	0.885	0.879	0.593
	ATT1	0.771		
	ATT2	0.788		
	ATT3	0.727		
	ATT4	0.781		
Subjective Norm (SN)	ATT5	0.781	0.895	0.624
	SN1	0.778		
	SN2	0.871		
	SN3	0.786		
Perceived Behavior Control (PBC)	SN4	0.860	0.868	0.621
	PBC1	0.727		
	PBC2	0.813		
	PBC3	0.803		
Future EV Purchase Intention	PBC4	0.807	0.855	0.596
	INT1	0.790		
	INT2	0.812		
	INT3	0.770		
	INT4	0.713		

Table 3. Discriminant Validity (HTMT)

Construct	CV	EV	EP	FV	SV	RE	RC	PS	PV	PBC	ATT	SN	TU	INT
CV	—													
EV	0.679	—												
EP	0.868	0.782	—											
FV	0.689	0.548	0.594	—										
SV	0.624	0.835	0.762	0.279	—									
RE	0.778	0.689	0.706	0.689	0.527	—								
RC	0.239	0.088	0.222	0.097	0.256	0.181	—							
PS	0.612	0.579	0.626	0.509	0.481	0.757	0.185	—						
PV	0.489	0.544	0.505	0.333	0.446	0.629	0.250	0.879	—					
PBC	0.844	0.575	0.831	0.670	0.546	0.765	0.190	0.622	0.447	—				
ATT	0.824	0.654	0.838	0.650	0.512	0.896	0.259	0.787	0.603	0.904	—			
SN	0.596	0.579	0.676	0.400	0.640	0.579	0.253	0.494	0.389	0.711	0.610	—		
TU	0.212	0.160	0.204	0.289	0.086	0.196	0.458	0.054	0.047	0.187	0.220	0.131	—	
INT	0.809	0.755	0.792	0.565	0.756	0.813	0.261	0.656	0.573	0.886	0.795	0.792	0.209	—

Table 4. Collinearity Assessment

Relationship	VIF	Result
Attitude toward EV → Future EV Purchase Intention	2.329	No multicollinearity concern
Conditional Value → Attitude toward EV	2.502	No multicollinearity concern
Conditional Value → Perceived Behavioral Control	1.023	No multicollinearity concern
Emotional Value → Attitude toward EV	2.393	No multicollinearity concern
Epistemic Value → Attitude toward EV	2.644	No multicollinearity concern
Functional Value → Attitude toward EV	1.732	No multicollinearity concern
Perceived Behavioral Control → Future EV Purchase Intention	2.523	No multicollinearity concern
Perceived Severity → Attitude toward EV	2.509	No multicollinearity concern
Response Cost → Perceived Behavioral Control	1.023	No multicollinearity concern
Response Efficacy → Attitude toward EV	2.284	No multicollinearity concern
Social Value → Attitude toward EV	2.399	No multicollinearity concern
Subjective Norm → Future EV Purchase Intention	1.593	No multicollinearity concern
Technology Uncertainty -> Future EV Intention to purchase	1.109	No multicollinearity concern
Technology Uncertainty x attitude -> Future EV Purchase Intention	3.221	Acceptable (moderate collinearity)
Technology Uncertainty x Perceived Behavior Control -> Future EV Intention to purchase	3.664	Acceptable (moderate collinearity)
Technology Uncertainty x subjective norm -> Future EV Intention to purchase	2.085	No multicollinearity concern
Perceived vulnerability -> attitude toward EV	2.187	No multicollinearity concern

Structural Model

Aggregate Structural Baseline

As an aggregate baseline, attitude ($\beta = 0.223$, $p < 0.001$), subjective norm ($\beta = 0.322$, $p < 0.001$), and perceived behavioural control ($\beta = 0.317$, $p < 0.001$) were positively associated with future EV purchase intention. The full structural estimates are reported in Supplementary Table S1. These coefficients are retained only to provide the reference point for evaluating latent heterogeneity.

The aggregate model explained 60.5% of the variance in future EV purchase intention, while the corresponding explanatory and predictive metrics for the aggregate model are reported in Supplementary Table S2. Because a full-sample estimate does not establish that the same coefficient pattern applies across owners, the subsequent FIMIX-PLS analysis evaluates whether this aggregate pattern conceals latent structural variation.

Interpretation of the FIMIX results is limited to variables reported at segment level. Demographic composition, mobility patterns, charging access, infrastructure exposure, and PMT or TCV paths are not used to label segments unless corresponding segment-level evidence is

available.

FIMIX-PLS Segmentation Results

FIMIX-PLS was used to assess unobserved heterogeneity in the structural model. The two-, three-, and four-segment solutions produced different model-selection signals. The estimated mixture proportions were 89.94% and 10.06% for two segments; 53.04%, 37.79%, and 9.18% for three segments; and 34.31%, 28.45%, 28.45%, and 8.79% for four segments. These percentages are estimated mixture proportions, not demographic group sizes.

FIMIX-PLS was employed to uncover unobserved heterogeneity in the structural model. The results of the model selection process presented in Table 5 indicate that different criteria suggest different numbers of segments.

Table 5. FIMIX Model Selection Criteria

Number of Segments	Segment proportions (%)	AIC3	BIC	CAIC	MDL5	EN	NFI
2	89.94 / 10.06	2636.64	2770.13	2811.13	3796.07	0.988	0.991
3	53.04 / 37.79 / 9.18	2475.94	2677.79	2739.79	4229.22	0.673	0.659
4	34.31 / 28.45 / 28.45 / 8.79	2446.94	2717.17	2800.17	4794.08	0.618	0.581

BIC and CAIC reached their minimum values for the three-segment solution (2677.79 and 2739.79), whereas AIC3 continued to decline and was lowest for four segments (2446.94). MDL5, entropy, and NFI favoured the two-segment solution. The two-segment solution also produced a markedly uneven estimated partition of 89.94% and 10.06%. The three-segment solution was therefore retained as a working specification because it combined the lowest BIC and CAIC with a less extreme distribution across its two largest components. This decision is not presented as uniquely determined: entropy declined from 0.988 for two segments to 0.673 for three segments, and the smallest component in the retained solution represented only 9.18% of the estimated mixture. The small third component is therefore interpreted cautiously in the subsequent segment-specific analysis.

The retained three-segment solution produced estimated mixture proportions of 53.04%, 37.79%, and 9.18%. Segment 3 was therefore considerably smaller than the two larger components. Its small estimated proportion, together with the near-boundary estimates observed for this component, warrants caution when interpreting its segment-specific coefficients. Accordingly, the subsequent interpretation focuses primarily on the two larger segments, while Segment 3 is reported descriptively without assigning it a stable behavioural profile.

The two larger segments therefore contain different descriptive decision patterns. Segment 1 is more strongly associated with perceived control in the retained model, whereas Segment 2 is more strongly associated with subjective norm. PBC has been associated with EV purchase intention in prior behavioural studies, but its relative importance is not constant across settings (Deka et al., 2023; Higuera-Castillo et al., 2023; Saputra & Andajani, 2023). Likewise, subjective norms and social influence have been linked to EV-related decisions, with their contribution varying across samples and cultural settings (Aksen & Kurani, 2012; Bhat et al., 2022; Cabeza-Ramírez et al., 2025; Deka et al., 2023). The present analysis does not provide formal between-segment coefficient tests, so these patterns are described as numerical differences rather than statistically established differences between segments.

Segment 3 requires a different level of caution. Its PBC coefficient is 0.833, subjective norm is 0.288, and attitude is -0.105, but future purchase intention has $R^2 = 0.9998$ and a residual variance of 0.001. Near-perfect fit also appears in the smallest component of the alternative two-segment solution ($R^2 = 0.9998$; residual variance = 0.001) and four-segment solution ($R^2 = 1.0000$ when rounded; residual variance = 0.001). The recurring boundary pattern indicates that the

smallest-component coefficients may partly reflect finite-mixture estimation behaviour. Segment 3 is therefore not assigned a substantive behavioural label.

The FIMIX output does not by itself identify why the two larger segments differ. Travel distance can affect how users evaluate the practicality of EV use, particularly when range requirements become more demanding. Charging availability can also influence whether EV use is perceived as feasible in everyday travel (Neaimeh et al., 2017). Affordability and financial considerations represent another source of variation in EV evaluation (Farajnezhad et al., 2024; Pandita et al., 2024). Infrastructure conditions may further shape the practical constraints faced by EV users (Egbue & Long, 2012). Segment-based EV studies have also reported differences in travel behaviour (Morton et al., 2017), charging styles (Hajhashemi et al., 2024), risk-related evaluations (Champahom et al., 2024), and preference structures (Zuo et al., 2025). These findings make several explanations plausible, but the coefficients reported here do not establish differences in charging access, travel distance, infrastructure reliability, income, or other observed characteristics because those variables were not used to profile FIMIX membership. Such explanations therefore remain hypotheses for subsequent profiling.

The same restriction applies to TCV, PMT, and technological uncertainty. TCV distinguishes functional, social, emotional, epistemic, and conditional values as separate dimensions of consumer choice (Sheth et al., 1991). PMT, by contrast, separates threat appraisal from coping appraisal through constructs such as perceived severity, vulnerability, response efficacy, and response cost (Prentice-Dunn & Rogers, 1986). These constructs operate in the aggregate model but are not reported as segment-specific paths in Table 6. Technological uncertainty is also relevant to EV evaluation. Concerns about driving range have been reported as a barrier to EV use (Egbue & Long, 2012), while financial and technological considerations can affect assessments of EV ownership (Farajnezhad et al., 2024). Technology-related uncertainty has also been examined in the Indonesian EV context (Lazuardy et al., 2024). The present discussion therefore does not infer that consumption values, protection-motivation appraisals, or technological uncertainty differ across segments unless those relationships are estimated at segment level.

Table 6. Segment-Specific Structural Results

Relationship	Segment 1 (53%)	Segment 2 (37.8%)	Segment 3 (9.2%)
Attitude → Future EV Purchase Intention	0.264	0.146	-0.105
Subjective Norm → Future EV Purchase Intention	0.096	0.468	0.288
Perceived Behavioral Control → Future EV Purchase Intention	0.497	0.135	0.833
R ² Future EV Purchase Intention	0.7159	0.4385	0.9998

The main analytical addition of FIMIX-PLS is narrower than the aggregate behavioural model. FIMIX-PLS is intended to identify unobserved heterogeneity in structural relationships rather than to replace the theoretical model itself (Ringle et al., 2015). Previous EV segmentation studies have classified users according to observable or latent characteristics. Morton et al. (2017), for example, identified consumer segments based on differences in EV-related characteristics and preferences. Hajhashemi et al. (2024) examined heterogeneity associated with charging behaviour, whereas Zuo et al. (2025) used a latent-class approach to distinguish patterns in EV purchase intention. The present analysis differs because the segmentation is derived from heterogeneity in the structural relationships themselves. For current EV owners in this sample, the aggregate coefficients for subjective norm and PBC are numerically similar, whereas the two larger latent

segments show different relative coefficient patterns for these predictors.

The retained segmentation should nevertheless be treated as exploratory. Model-selection criteria do not converge on the same number of segments. BIC and CAIC favour the three-segment solution, whereas other criteria provide support for alternative specifications. Classification quality also declines from the two-segment to the three-segment solution, as reflected in the lower entropy value. In addition, the smallest component approaches a residual-variance boundary, which raises concern about the stability of that segment. These features limit claims that the three components represent fixed population subgroups. Replication with an independent sample of current EV owners, repeated mixture estimation, and formal procedures for comparing segment-specific coefficients are therefore needed before stable segment labels are assigned.

Practical interpretation should remain tied to the observed coefficients. In Segment 1, PBC has the largest estimated proximal coefficient, which is consistent with a stronger role for perceived manageability in future EV purchase intention. Prior EV research has linked charging accessibility to the practical feasibility of EV use (Foley et al., 2020; Sierczula et al., 2014). Financial constraints can likewise affect whether EV ownership is perceived as manageable (Farajnezhad et al., 2024). In Segment 2, subjective norm has the largest estimated proximal coefficient, which is consistent with a stronger role for perceived social expectations. Social influence has been associated with EV-related decisions in previous studies (Axsen & Kurani, 2012; Bhat et al., 2022). Its contribution, however, can vary across behavioural contexts and samples (Deka et al., 2023). These comparisons provide theoretical context for the observed coefficients; they do not establish that specific infrastructure, policy, communication, or service interventions would alter the relationships identified in this cross-sectional model.

Conclusion

FIMIX-PLS identified a three-segment working solution for future EV purchase intention among 521 current EV owners in Jabodetabek. The retained solution had estimated mixture proportions of 53.0%, 37.8%, and 9.2%. PBC had the largest proximal coefficient in Segment 1 ($\beta = 0.497$), whereas the subjective norm had the largest coefficient in Segment 2 ($\beta = 0.468$). These patterns provide segment-specific information that is not visible in the aggregate model, but they are numerical differences rather than formal tests of coefficient differences.

The smallest retained segment should not be interpreted as a stable behavioural type without further evidence. Its future-purchase-intention R^2 is 0.9998 and its residual variance is 0.001, a boundary pattern that also appears in the smallest components of the two- and four-segment alternatives. The purposive, cross-sectional design further limits population generalisation and causal inference. The study also does not distinguish replacement, repurchase, and additional-purchase intentions among current owners.

Future analysis should test whether the two larger latent patterns replicate in an independent sample of current EV owners and should compare segment coefficients with an inferential procedure rather than coefficient magnitude alone. If segment membership is exported reliably, demographic and mobility variables can then be used for external profiling. Objective charging accessibility, travel behaviour, and subsequent vehicle purchases would be needed to determine whether the latent behavioural patterns correspond to transport-system conditions or actual purchasing behaviour.

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